

# Optimization-based Method for Automated Road Network Extraction

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**Abstract:** Automated road information extraction has significant applicability in transportation. It provides a means for creating, maintaining, and updating transportation network databases that are needed for purposes ranging from traffic management to automated vehicle navigation and guidance. This paper is to review literature on the subject of road extraction and to describe a study of an optimization-based method for automated road network extraction.

## ***1. Introduction***

Automated road information extraction has significant applicability in transportation. It provides a means for creating, maintaining, and updating transportation network databases that are needed for purposes ranging from traffic management to automated vehicle navigation and guidance. Until today, road network extraction still heavily depends on human labors, which makes network database development an expensive and time-consuming process. Automated road information extraction from high-resolution images holds great potential for significant reduction of database development cost and turnaround time, and vigorous efforts have been made to develop better algorithms and methodologies for this purpose.

Nevertheless, development of reliable procedures remains challenging. The technical difficulty in general is that high-level image understanding is essential to road recognition, but high-level image understanding cannot be achieved without low-level image understanding. On the other hand, road recognition from local images is difficult because global network properties cannot be utilized. Further, image understanding itself is error-prone, and images of real scenes frequently contain incomplete and ambiguous information. When factors such as image resolution, degradation of image quality, obstructions, and presence of linear but non-road features are taken into consideration, the task of road identification becomes overwhelmingly complex.

This paper describes an optimization-based method for road network extraction problem. The paper is organized as follows. Section 2 provides a literature review that summarizes important research efforts on the subject of road information extraction. The purpose of literature review is to establish a basic understanding of the state-of-the-art of methodologies used in road network

extraction. Section 3 presents the results of road characteristics studies, focusing on road image intensity, image texture and geometric characteristics. This study serves as a modeling aid for the optimization-based extraction. That is, through the analysis of road image characteristics, image models can be established and utilized to facilitate more reliable road recognition. In section 4, the test with a road extraction method that uses dynamic programming and supervised classification is described and the results are illustrated. And finally, section 5 provides a summary and some discussions about the overall results and sheds some light on future research directions.

## **2. Literature Review**

Because of its significant applicability, automated road information extraction from satellite and aerial imagery has been an important subject of research in remote sensing. The current effort is particularly interested in road network extraction using pattern recognition approaches. The reason is that most applications involved in safety, hazards, and disaster assessment requires detailed and accurate representations of road networks, which can only be obtained from high-resolution images. However, these types of images are mostly panchromatic, such as Digital Orthophoto Quadrangles (DOQ) from U.S. Geological Survey (USGS), and one-meter resolution IKONOS images from Space Imaging. Their spectral signatures are weak and can not be effectively utilized to identify road features. Instead, image interpretation has to rely on image texture, shapes, patterns and changes of local image intensity.

In the last twenty years or so, a variety of extraction methods have been developed. Some of them can be generally applied for linear feature extractions, while others are particularly designed for the road extraction task. The report classifies these methods into five categories: ridge finding, heuristic reasoning, dynamic programming, statistical tracking, and map matching. It is worth noting that such a classification is mainly for generalization and convenience of description. Actually, it is very difficult to classify some of these methods into specific categories. For instance, some of the existing algorithms may use a combination of different methods. And in some other cases, a method may fall into several method categories.

### **2.1. Ridge Detection**

Intuitively roads are linear features that are shown as ridges or valleys on an image. Therefore road finding can also be considered as a task of ridge finding. The procedure developed by Nevatia and Babu (1980) is a classic one, which starts with the convolution of an image with a number of edge filters to obtain edge magnitude and direction, then goes through a thresholding and thinning process in order to delineate edge pixels, and finally connects the delineated edge pixels to form linked line segments. Gradient Direction Profile Analysis (GDPA) (Wang et al. 1992; Gong and Wang, 1997) is another representative method used for ridge finding. This method first calculates the gradient direction for each pixel, which is defined as the direction of maximum slope among the four defined directions near the pixel. As the ridge direction has the same direction as a road segment or a linear segment, and it is perpendicular to the gradient directions of the pixels with the ridge, an analysis of the gradient profile will generate the ridge pixels, which correspond to the highest points of the profile. Linking the ridge points then produces the ridgelines, or in the road detection case, the road segments.

The concept of differential geometry has also been applied to ridge detection (Steger, 1996). This method uses curve or surface fitting techniques to derive ridge locations on an image. Once the image intensity surface is represented with a mathematical equation, the first and the second derivatives of the equation can be analyzed to locate ridgelines. Image filtering methods have also been extensively discussed in the literature for edge or ridge delineation. Most frequently referenced methods in this category include Canny's edge detector (Canny, 1986) and Marr and Hildreth's zero crossing operator (Marr and Hildreth, 1980). These methods filter out the low-frequency information in the image and preserve the high-frequency structures, such as roads, which are particularly useful for high-level recognition of road networks because through image filtering, a large amount of information that is irrelevant to road recognition can be thrown away at the very beginning, and then image analysis can focus on these structures that contain road networks.

## **2.2. Heuristic Method**

The heuristic method makes use of a reasoning process similar to the human vision system. Sometimes it is also referred to as rule- or knowledge-based method. Melsels and Mintz (1990) considered a three-stage reasoning concept and applied the concept to road network extraction: a low-level stage that deals mainly with pixel segmentation, a high-level stage that models and labels feature objects, and an intermediate level of representation that interfaces between low-level and high-level processing. Image primitives that are considered as building blocks of roads are first identified with pixel value checking at neighborhood levels. Intermediate level analysis will combine image primitives into line segments with the use of some reasoning mechanism (e.g., how far the combined primitives are apart; what directions each of the primitives follows; whether they parallel with each other; etc). High level processing allows further gap filling and segment grouping by considering distances, brightness, and uniformity among the grouped tokens and gaps between them.

One of the advantages of the heuristic approach is in its flexibility in dealing with problems such as linear feature alignment and fragmentation. For example, McKeown and Pane (1985) suggested that trend and the relative distances between fragments can be utilized as factors while fragmented primitives are aligned and connected. With some extension, McKeown and Denlinger (1985) also developed a road tracking system that relies on road texture correlation and road edge following alternatively: when one fails, the other will be utilized. Later, McKeown et al (1992) and (Zlotnick, 1993) introduced methods that track roads by searching for anti-parallel edges as starting points for road tracking and linking.

## **2.3. Dynamic Programming**

Dynamic Programming (DP) has been frequently utilized in road network extraction and has been described in detail by Gruen and Li (1996). The most appealing aspect of the method is that the road recognition problem can be formulated as an optimization program, and the solution to this program will result in the delineation of the road pixels. According to Gruen and Li, roads can be modeled with a set of mathematical equations. That is, derivatives of the gray values in the direction normal to the roads tend to be maximized, while derivatives along the road

direction tend to be minimized. At the same time, roads tend to be straight lines or smooth curves, normally circular arcs, and their local curvature has an upper bound. These properties, then, can be characterized with a merit function, which can be solved using the DP technique.

The introduction of the DP technique in pattern recognition dates back to the late 1960s. Since then, the technique has been used on raw images for pixel based processing (e.g., Montanari, 1970), and also used on tokens that are based upon higher level representations (Fischler et al, 1981; Geman and Jedunak, 1996). The technique is considered to be a good approach to finding curves in noisy pictures, because it can bridge weakly connected feature elements automatically while the program searches for optimal solutions. This property is also preserved when applied to the grouping of feature elements with higher level of representations. In either case, regulatory constraints can be utilized to derive curves that will meet certain predefined geometric requirements (e.g., smoothness or curvature). More importantly, DP provides a way to serialize the optimization procedure to allow computationally attainable solutions.

## **2.4. Statistical Inference**

Due to complexities of road images, an ability to handle uncertainties (e.g., bridge crossing, road width changing, cars and shadows on the roads, image noises, etc.) is essential. For this reason, statistical models are particularly attractive for road image representation. Cooper (1979) first came up with the idea of modeling a blob boundary or a linear feature as a Markov process. Based upon this modeling scheme, he was able to use maximum likelihood estimation to derive the boundary representation that has the same formulation as other deterministic methods. The underlying significance of Cooper's scheme is that it provides an elegant and effective methodology for incorporating uncertainties into the linear feature recognition process.

Barzohar and Cooper (1996) explored the idea further and developed a stochastic approach that can be more sophisticatedly applied to automatic road finding. This approach makes use of the so-called geometric-stochastic model that formulates road width, direction, gray level intensity, and background intensity as a stochastic process using the Gibbs Distribution. Then road detection is achieved through the maximum a posteriori probability (MAP) estimation. The method demonstrated promising results and can be further extended to consider possibly many other types of uncertainties in road extraction. A more recent study by Yuille and Coughlan (2000) provides additional enhancements to Barzohar and Cooper's approach. This study not only allows the analysis of the time and memory complexity in the MAP estimation, but also the determination of whether roads are detectable in a given image.

The work of Geman and Jedynak (1996) is also based upon a statistic model that tracks roads through hypothesis testing. Their approach uses the testing rule that is computed from the empirical joint distributions of tests (matched filters for short road segments) to determine whether the hypothesis (road position) is true or not. The tests are performed sequentially and a uncertainty or entropy minimization procedure is devised to facilitate testing decisions, so that new tests can be analytically identified. The method appears to work reasonably well on low-resolution images, but likely adaptable to high resolution images as well.

## **2.5. Map Matching**

The rationale behind map matching in road extraction is that there already exists a large amount of data on road systems in many parts of the world, especially in the United States. Once in house, this data can serve as a starting point for road network extraction. There are many advantages to combining remotely sensed data with existing databases (Wang et al., 1992). That is, existing data can be used as the interpretation key at the beginning, then verified, or updated, and the attributes of existing network can be also transferred to the newly updated network.

The map matching approach has been explored by several researchers (Maillard and Cavayas, 1989; Stilla, 1995; Fiset et al., 1998; Zafiropoulos, 1998). Maillard and Cavayas first introduced the map-matching approach. Using this approach, they established a road updating procedure that consists of two major algorithms. The first algorithm focuses on image-map matching to identify roads that can be found on the map and the image. The second algorithm is then to search new roads based upon the assumption that these new roads are connected to the old ones. This approach was studied further and applied in different geographic settings (Fiset and Cavayas, 1997). To overcome some of the map matching problems of this approach, Fiset et al (1998) used a multi-layer perceptron based upon template matching to improve its performance further.

Stilla developed a syntax-oriented method to use the map knowledge as a supportive aid for image interpretation. In this study, representations of road network structures are first obtained through map analysis. Then image object models are defined and utilized to search for objects that fulfil model expectations with a given tolerance. Assessment on image objects with respect to its correspondence to the map representations results in road object identification for a given image scene. Zafiropoulos (1998) considered the concepts of deformable contours, B-Splines, Ribbon Snakes and presented a mathematical-modeling-based road verification and revision framework. With this framework, road centerlines are localized using a global least square adjustment.

## **2.6. Summary**

From the above review of the existing methods on road network extraction, several observations can be made. First, the concept for road network extraction is relatively simple. That is, roads are shown as ridges and valleys; image intensity changes little along a road, but change drastically while cutting across a road; road direction changes tend to be smooth and have an upper bound; and roads follow some topological regularities in terms of connectivity among themselves. Basically, many of the existing methods make use of one or several of these characteristics.

Second, reliable road network extraction remains a difficult task, and there exists no algorithm sufficiently reliable for practical use (Geman, and Jedynak, 1996). This is primarily due to the fact that the real world is too complex, and many of the existing tools can only handle very specific cases. Some may be able to handle more complex situations, but still can not be compared with a trained human operator. Mathematical models such as statistical models and dynamic programming have enhanced the ability to deal with this complexity significantly, but

factors such as computational performance, implementation difficulty, and limitation of sophistication make more ambitious efforts difficult. Theoretically, a road recognition algorithm can consider all possible listed road characteristics. Practically, a road recognition algorithm can only consider a limited set of characteristics, and when these characteristics change beyond a limit, the algorithm may fail.

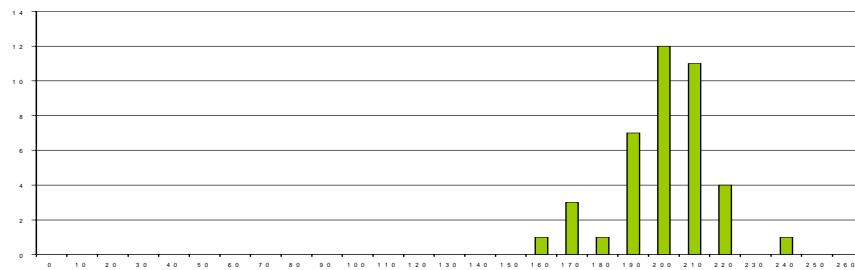
Finally, even though automated road extraction is a difficult problem to solve, improvement has been constantly made and there are still opportunities to be explored to further improve its performance. It appears that the semi-automated and the map-matching-based approaches tend to be more practical for short-term implementations. In the long run, studies of road image characteristics, their changes with respect to geographic background, image types, image resolutions, and development of mathematical models to represent these characteristics are critical in order to make substantive progress in this area.

### 3. Road Image Characteristics

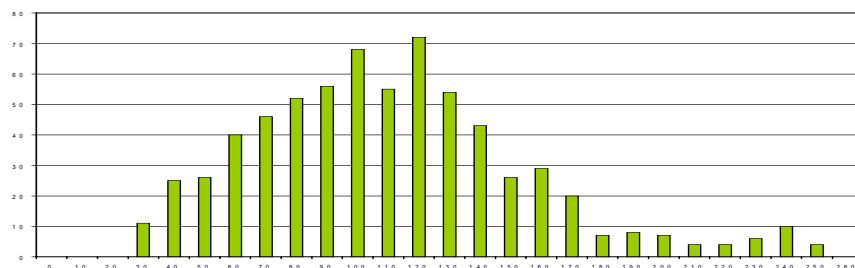
The mechanism that allows human vision to easily differentiate roads from the background on an image is straightforward. That is, we know what a road looks like and we know many different types of roads. We also know the differences between a road and a river stream, and know that there might be cars, patches, tree shadows, and even people on the roads. In addition, we know the relationships between the roads and other earthly features. With all of this knowledge in mind, we can identify, verify, track, and guess whether something on an image looks like a road. Mistakes are made sometimes, but for a well-trained human operator, the chance of mistakes is small. To allow the computer to do the same job, similar knowledge about road networks is required. The study of road image characteristics aims to acquire this knowledge in a form that is amenable in a computational environment. The current research focuses on three types of road characteristics: image intensity, texture, and road geometry.

#### 3.1. Image intensity

In general, image intensity can not be used alone for reliable road recognition on black and white images. However, consistency of image intensity on road pixels is a basic assumption that has to be made for road recognition. That is, road pixels can be dark, or white, or have intensity values in any specific intensity range, but still we expect to find representative gray values on road pixels. This expectation by no means assumes uniformity of gray values on road pixels. Image intensity on a road may fluctuate due to the presence of cars, manholes, bridges, and tree shadows. Different types of roads on the same image may still have different representative gray values. And different locations of a single road may also have different representative gray values due to conditions such as different pavement materials. However, gray values along roads will not change frequently.



**Figure 1 (a). Histogram of intensity values for on-road pixels.**

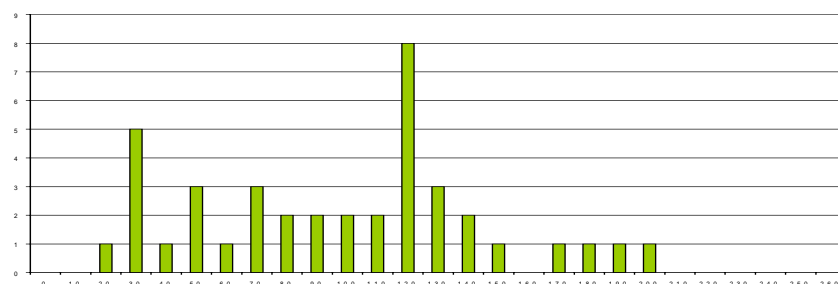


**Figure 1 (b). Histogram of intensity values for off-road pixels.**

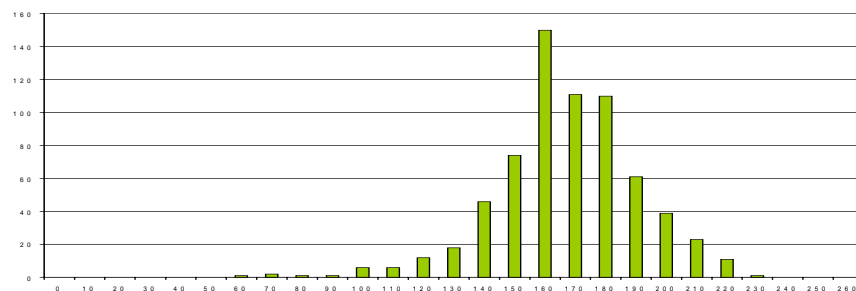
Figure 1 (a) and (b) show the comparison of two gray value histograms: one obtained for road pixels, and the other obtained for off-road pixels. The differences of statistical characteristics (e.g., median, maximum, and minimum) of the two diagrams are obvious. The point made here is that gray values for on-road pixels do have some special characteristics, and they are more frequently found in a given range. Obviously, the consistency property of gray values on road pixels is a valuable evidence for road identification, and may not be neglected while the pattern recognition approaches are applied.

### 3.2. Texture measures

Given the difficulty in separating road pixels from non-road pixels with image intensity values, texture analysis has proven particularly useful in enhancing the segmentation performance (Haralick, 1973; Marceau, 1989; and Gong et al., 1992). The basic idea of texture analysis is to identify distinguishable spatial patterns between different features (e.g., between roads and non-roads). Texture measures can be derived for different scales, the immediate neighborhood of a pixel, an image region or an entire image. In the current study, we focus on the immediate neighborhood of a given image pixel. This is based on the consideration that roads are limited in their widths, texture measures over more extensive areas may not be effectively utilized for road pixel segmentation.



**Figure 2 (a). Histogram of intensity values for on-road pixels.**



**Figure 2 (b). Histogram of intensity values for off-road pixels.**

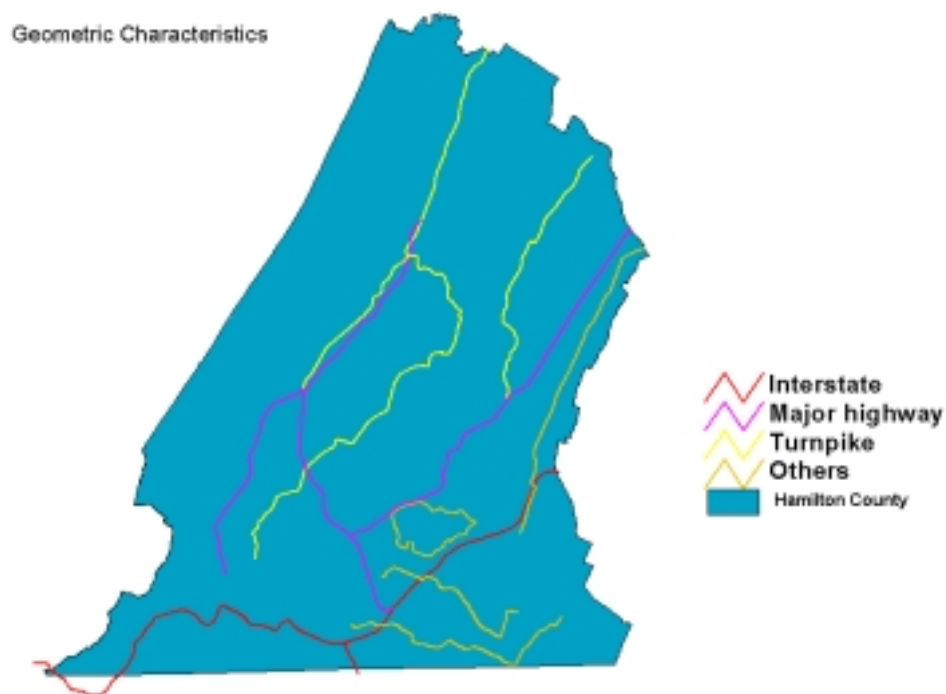
Seven different texture indices have been generated to compare the differences between texture measures for on-road and off-road pixels, including intensity average, entropy, homogeneity, contrast, energy, maximum probability and standard deviation. For example, Figure 2 shows the histograms of entropy intensity values for both on-road and off-road pixels. From these histograms, it is understood that the entropy values of on-road pixels are low and are spread relatively evenly across their spectrum. In contrast, the entropy values of off-road pixels are high

and concentrate on a specific value range. The general observation for all the texture measures is that: image intensity on road pixels is more consistent and their texture measures tend to have constant values on intensity average, low values on entropy, high values on homogeneity, low values on contrast, and constant values on energy, low values on maximum probability and low values on standard deviation.

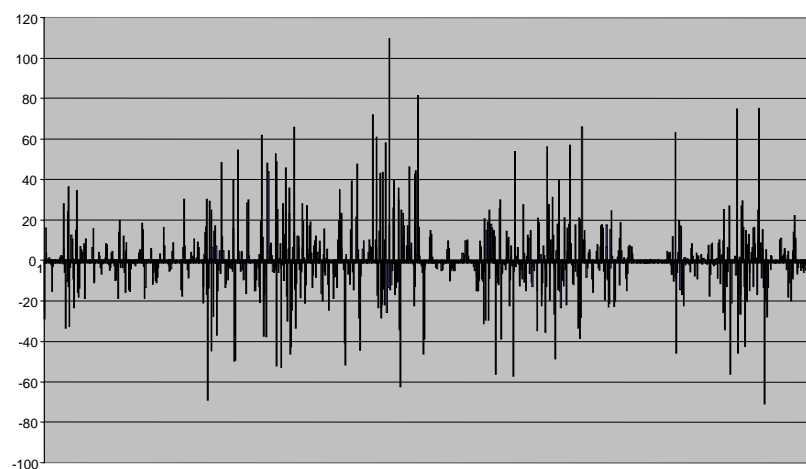
### **3.3. Geometric characteristics**

Road geometric characteristics include road width, curvature, and grade characteristics. From a design point of view, road geometry must conform to highway design standards in order to meet efficiency and safety requirements. Nevertheless, an understanding of these characteristics as to how they are represented in the real world would be useful for road model development because geometric characteristics change, when geography or environmental settings change, even when the standards used for the road design are the same.

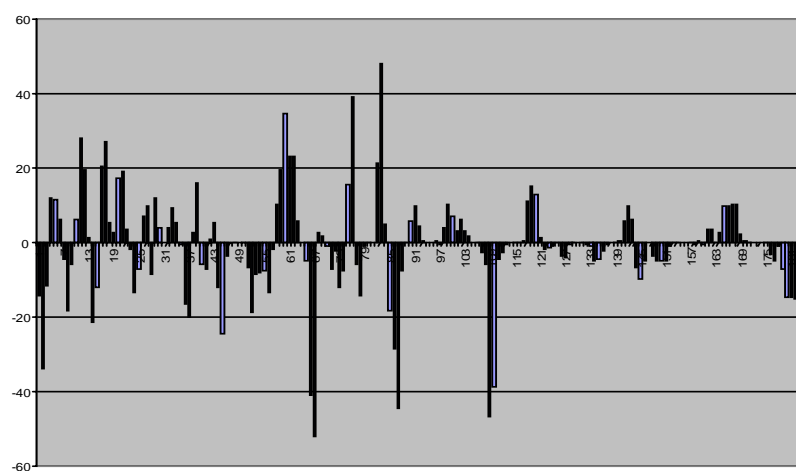
Considering major road geometric characteristics, road width is an important geometric parameter. However, this parameter can be more effectively handled through a prescriptive approach. That is, the road width or a width range can be directly defined as an input constraint in the road extraction process. For this consideration, road width will not be included in our analysis. The grade is another important geometric parameter, but appears difficult to deal with. At minimum, accurate 3D models will be required for the study of the grade characteristics. Data of such type is still fairly expensive. For these reasons, the present study only considers road curvature.



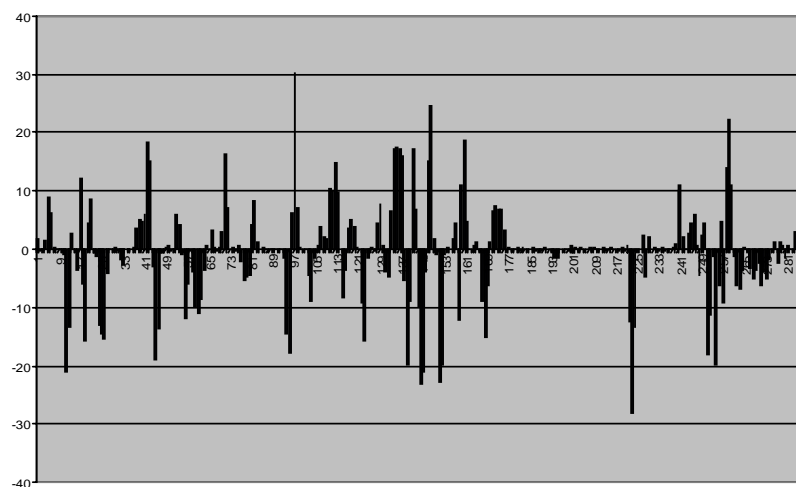
**Figure 3. Selected road networks in Hamilton County, Tennessee.**



**Figure 4 (a). Directional change characteristics for all types of roads.**



**Figure 4 (b). Directional change characteristics for interstates.**



**Figure 4 (c). Directional change characteristics for major highways.**

To study the road curvature, a road network database provided by GIS Department of Hamilton County, Tennessee was utilized. Figure 3 shows the road networks used for the study, and Figure 4 shows the road curvature changes for different types of road networks. The vertical direction in these diagrams represents the degree of changes per 1000 feet, and horizon directions represents the number of observations accumulating from the origin where the measurement starts. Several points are worth noting. First, curvatures can be measured with the rate of directional changes along a road, and this rate highly depends on the linear unit utilized for the measurement. The use of different linear units will likely generate different curvature characteristics. Second, there is an aggregate factor involved in the curvature calculation. That is, when longer linear units are utilized, computed curvature can get smoothed, which is the same effect that can be achieved by map generalization. Third, roads that are found in different geographic backgrounds likely have different curvature characteristics. For this reason, geographic variation needs to be considered as a variable in the study of road geometric characteristics as well, which will be a future research topic.

### **3.4. Summary**

The study into road image characteristics provides some useful results that allow us to characterize images more accurately and develop more effective extraction models in a latter stage. The study shows that image intensity values still contain important information about the presence of roads. Texture measures such as intensity average, deviation, and entropy are also useful in distinguishing road and non-road pixels. Geometric characteristics such as road width and curvature can be provided in a prescriptive way, such as defined directly from the input, but study of these characteristics such as curvature will provide useful constraints or regulatory rules used in the road extraction process.

## **4. Test and Experiment of Road Network Extraction**

Through previous research, ORNL has developed an optimization-based road extraction framework. In the current research, we intend to improve this framework in two major areas. One is to incorporate findings from the study of road characteristics, and another is to refine a supervised recognition procedure for the road network identification process. Plausibly, many existing approaches use prescriptive property of road images in road extraction, which can simplify the extraction procedure, but is not reliable when road image characteristics change. The current method is based upon road characteristics that are directly found on the same image or images that are similar to the images from which roads will be extracted. The supervised recognition procedure then takes advantage of these characteristics to establish a training process, so the computer will be able to learn from these characteristics directly. This procedure is also an improvement to many existing approaches. It will not treat curves that are identified initially as roads directly. Additional verification with the supervised recognition is implemented to allow more reliable identification.

In this section, the recognition mechanism is reviewed first. Then the results of the test and experiment are described.

#### 4.1. Road Extraction Formulation

In ideal situations, when image intensity is measured along road pixels, little or no change will be observed. In contrast, drastic variations will be expected when image intensity is measured for pixels cutting across the road. Also roads are usually represented by straight lines or smooth curves, which means that the first and the second derivatives of the road curves will have an upper bound. Continuity is another important characteristic for roads. That is, aligned road segments are likely connected. This characteristic forms a critical assumption when portions of roads become invisible and need to be delineated through extending its neighboring segments.

For computational purposes, the above described road characteristics can also be expressed in mathematical functions. Let  $Z(p, q)$  denote the intensity function of an image. To start with, let  $F_u(Z)$  represent the directional derivative of  $Z$  along  $u$ , naturally  $F_u(Z) = |dZ/du|$ , and  $F_n(Z)$  represent the directional derivative of  $Z$  along  $n$ ,  $F_n(Z) = |dZ/dn|$ . (We use absolute values to ensure that  $F \geq 0$ .) The smoothness along a road segment can be expressed as, also reference to Gruen and Li (1997):

$$\min_{e \in E} F_u(Z) = \int_0^{Se} |dZ/du| du. \quad (1)$$

And the rapid changes perpendicular to a road section can be denoted as:

$$\min_{e \in E} F_n(Z) = \int_0^{Se} |dZ/dn| du. \quad (2)$$

Similarly for angular and continuity constraints:

$$\min_{e \in E} F(\theta) = \int_0^{Se} |d\theta/ds| du, \quad (3)$$

and

$$\min_{e \in E} F(\theta') = \int_0^{Se} |d^2\theta/ds^2| du. \quad (4)$$

To recognize a road on an image, a road segment can be defined as an ordered pair  $\{k, l\}$  where  $k$  denotes the starting point, and  $l$  denotes the ending point. Further we define  $C = [V, E]$  as a curve that connects points  $\{k, l\}$ , where  $V$  is an ordered set of points and  $E$  is an ordered set of segments. Now, let  $v = \{p, q\}$  denote the centroid of a pixel, and  $v \in V$ , and let  $e = \{i, j, s, u, n\}$  denote a segment connecting two neighboring centroids and  $e \in E$ , where  $i$  and  $j$  are the starting and ending points of a segment,  $s$  is the segment length,  $u$  represents the segment direction, and  $n$  represents the direction perpendicular to  $u$ . Because many curves may connect points  $\{k, l\}$ , we define a superset  $\mathcal{P}(C)$  that represents all possible curves, hence,  $C \subseteq \mathcal{P}(C)$ . For convenience,

we define  $C^*$  as a set of potential road curves. Our task, then, is to find a curve  $C$  so that  $C$  connects points  $\{k, l\}$  and  $C \subset C^*$ .

Assume there exists a property set,  $S = \{s_1(Z), s_2(Z), \dots, s_m(Z)\}$ , that can be used to measure the potential of the road presence, a curve that can best represent a road segment between  $\{k, l\}$  may be expressed as:

$$\min F(S) = \varphi(F_1(s_1(Z)), F_2(s_2(Z)), \dots, F_m(s_m(Z))). \quad (5)$$

Dynamic programming (DP) can now be utilized to provide an optimal solution to the problem. The use of the principles of optimality has obvious advantages. If the formulation is posed correctly, the derived curve should at least give the best outcome. More importantly, in noisy conditions, the formulation can provide approximate locations for obstructed roads. This is necessary in order to combine poorly connected image pixels to form a connected segment, and to fill gaps that should not exist in the first place.

To establish positive identifications for the derived curves, we propose another layer of formulation that treats the curves derived from the previous formulation as unknown objects. Let  $Y$  represent a finite set of attributes that are obtained from a curve or curves derived from the previous formulation, and we assume  $Y = \{y_1, y_2, \dots, y_m\}$ . Let  $X$  represent a set of class types that a curve or curves may represent, and we assume  $X = \{x_1, x_2, \dots, x_n\}$ . This research has devised a supervised classification scheme, with which for a given attribute set  $Y$ , a curve or curves can be classified into a class,  $x$  ( $x \in X$ ).

This supervised classification is actually based on a classic unsupervised clustering algorithm, the Iterative Self-Organization Data Analysis or ISODATA. The idea is fairly simple. When samples are first given to the algorithm, there are two major categories: roads and non roads. Because the distance to the centroid of a cluster is used as the criterion to determine whether the sample belongs to a cluster, and because the clusters are not well organized at the beginning, there is a good chance that some samples will be misclassified. To reduce misclassification, an iterative splitting and reorganization mechanism is devised to form new clusters to allow better-organized clusters. Eventually for the newly created clusters, each will represent a subcategory of features that have coherent feature attributes. At this point, each of the subcategories is mapped back to the category type given by the samples. Because of the use of the mapping procedure, feature categories can be more accurately represented by homogeneous feature characteristics internally, and higher classification accuracy can be achieved.

## **4.2. The Test and Experiment Procedure**

Digital orthophotos that were provided by the GIS Department of the Hamilton County, Tennessee, were utilized in the current experiment. The digital orthophotos were made available with two types of resolutions: two-foot ground resolution and six-inch ground resolution. The two-foot ground resolution images were used in the test. Hamilton County GIS Department also provided an accurate road network database, which is valuable for result validation and verification of the experiment

The implementation of the above mentioned procedure takes three major steps as shown in Figure 5, and each step is described briefly below.



**Figure 5. Steps for Road Extraction**

**Sampling:** This is the process from which road image samples are obtained. The process can be conducted either manually or semi-automatically. For a manual process, an operator can directly pick up road segments or road pixels. For a semi-automated process, an automated algorithm can run a preliminary search on an image to generate some primitives, then a human operator will select those primitives that are recognized as roads, then the selected primitives are used as road samples. The latter process is actually used in the current test.

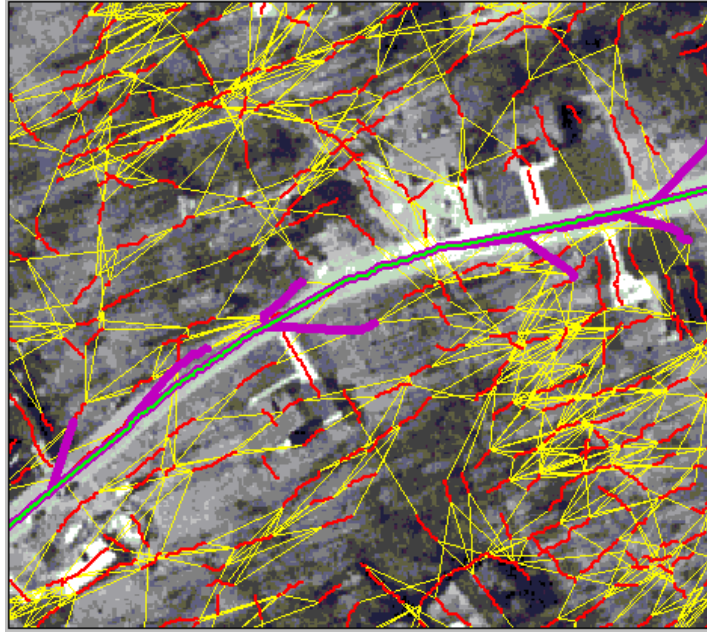
**Model Training:** Model training is a process of knowledge acquisition and model adaptation. After road image samples are obtained, these samples are used to extract road image characteristics (e.g., image intensity and texture measures). The ISODATA based training process is applied to learn these characteristics.

**Road Detection:** During the road detection stage, the program first runs a template-matching procedure that localizes potential road pixels, followed with the optimization as described in section 4.2. The purpose of this procedure is to identify all potential road segments, including non-road linear features. To allow a more inclusive search, a relaxed road model is utilized during this search. After this search process, all segments found will be considered as a road candidate. Then the supervised ISODATA classification procedure is applied to identify whether a candidate is a road or not a road.

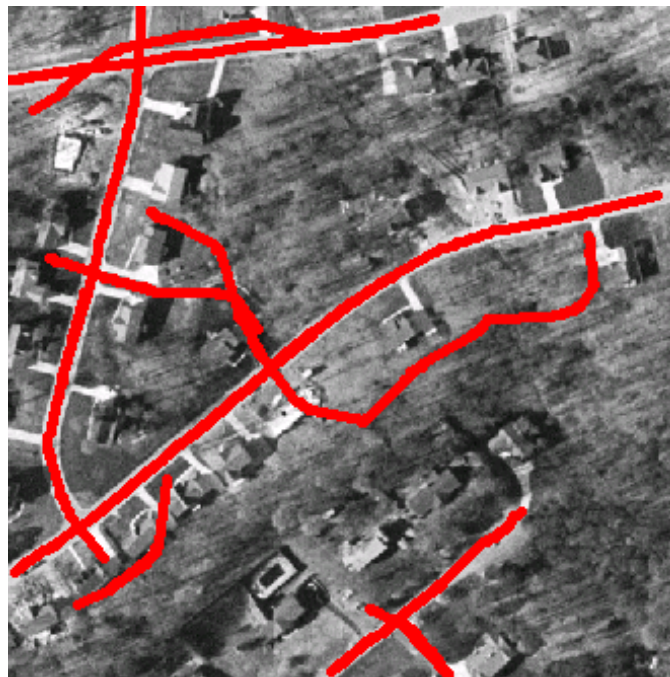
### **4.3. The Results**

Figure 6 through Figure 8 provide the results of the extraction experiment. Figure 6 is an illustration of the output from the dynamic programming. For computational performance, template matching that acts like a filter is applied to identify all potential road segments. After that, the dynamic programming procedure is utilized to render potential road curves, and these curves are shown in Figure 7. And finally, detected curves are classified into two categories, roads and non-roads, with the supervised ISODATA, Figure 8. A visual inspection of the results reveals that major roads on the given image are correctly identified and accurately localized.

The ISODATA algorithm used only three types of image characteristics for the supervised classification: intensity, average intensity, and entropy. Other texture measures and road geometry can be utilized as well, but the three characteristics utilized are sufficient to establish the road identity. Apparently after dynamic programming, the identified curves can be easily compared with the known road characteristics, and this comparison likely generates positive identifications.



**Figure 6. Template matching and dynamic programming.**



**Figure 7. Curves identified as road candidates.**



**Figure 8. Road classification (green lines are identified are roads, while purple ones are not).**

## ***5. Conclusions and Discussions***

Automated road network extraction is an important, but challenging, problem to solve. From the literature review, it is observed that a variety of methods have been developed for this purpose. So far there exists no method sufficiently reliable for practical use. The use of mathematical models such as statistical models and optimization techniques represents a major trend in the development of road extraction algorithms, but such models need to be further improved for sophistication, simplicity, and better performance. The study of road image characteristics aims to understand the road image characteristics with respect to image intensity, texture and geometric characteristics, which provides some useful results that allow us to characterize images more accurately. The extraction method using these results appears to provide good output.

The current research also intended to improve an optimization-based extraction framework in two major areas. One is to incorporate findings from the study of road characteristics, and another is to refine a supervised recognition procedure for the road network identification process. The test and experiment demonstrate that these considerations can generate reliable results and allows reasonable computational performance.

In spite of these positive results, it must be pointed out that there are several areas where additional research and development efforts will be necessary. First, the current research is still limited to a specific type of image and a particular geographic area. In order to use the method

for different types of images and in different geographic areas, comparisons of road image characteristics for different images and in different geographic areas would be very useful. Second, automated model training is still a weak area in the current research. ORNL has experimented with a map-matching approach to address this problem. The critical issue is the matching reliability (e.g., if something goes wrong with the map matching, things can get worse in the learning stage). For that reason, a robust verification mechanism must be devised in order to purify samples that are obtained from the matching procedure before they are sent to the training process. Third, the current research has specifically focused on a particular methodology. The approach used by McKeown and Denlinger (1985) appears extremely attractive. That is, alternative methods are coordinated to perform the extraction: when one fails, the other will be utilized.

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